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Towards health monitoring of hybrid ceramic bearings in aircraft starter/generators

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Abstract

On-board electrical power demands in modern aircraft are substantially increasing. Scaling-up the size of the current starter/generators to provide the additional power requirements inevitably increases their mass. Instead, aircraft electrical designers are considering to increase the rotational speed of these machines. This imposes severe loading demands in the current starter/generator bearings. Hybrid bearings offer the most potential to deal with these demands. However, not much is known about their wear behavior in this new application.
Our research is assessing the degradation of hybrid ceramic bearings in the newest generation of starter/generators for condition monitoring and health management. This paper discusses bearing degradation as foundation for the definition of relevant health condition assessment and decision making approach, and the integration of a monitoring system into a prototype test bearing to be used for data generation and algorithm validation. Initial results indicate this approach can effectively diagnose bearings faults. Validation was conducted by using repository data.

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Keywords: healh management; data-fusion; hybrid bearings; starters; generators; diagnosis

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1. Introduction

Driven by higher availability demands and optimization of maintenance tasks, aircraft manufacturers have been gradually adopting health monitoring systems for an increasing number of sub-systems and components. Starter/generators are an important component of aircraft engines; they initiate the engine operation and provide power to other aircraft systems too. Starter/generator bearings are generally replaced at scheduled preventive maintenance intervals. Their health monitoring will help reducing unnecessary maintenance tasks, and optimize maintenance schedules.

Modern aircraft require more on-board electrical power than ever before. Increasing the size of starter/generators to provide these additional requirements inevitably increases their mass. Instead, starter/generators manufacturers are considering increasing their operational speed. The rotational speeds of the newer generation of starter/generators are expected to approach 30,000 rpm. This will impose severe loading demands on the currently employed bearings; which can lead to earlier degradation due to harsher rolling contact fatigue (RCF). Additionally, bearings in starter/generators experience severe operational conditions, e.g., extreme temperature, vibration and electrical interference. In response to these new requirements, bearing designers are turning to hybrid bearings for the newest generation of starter/generators. However, not much is known about hybrid bearings wear behavior in this application.

Hybrid bearings are typically constructed using rolling elements made of a ceramic material such as silicon nitride, running over fatigue resistant steel raceways. Critically, ceramic materials' mass can be up to 60 % lower than that of conventional ball bearings, resulting in lower centrifugal loading and skidding [1]. Some of the most recognized performance benefits of hybrid bearings include [2]: higher rotational speed, longer life, lower heat generation and superior starvation tolerance.

1.1. Research program objectives

The overall objectives of our research are:

1. Identification of relevant condition indicators for health monitoring of hybrid bearings in starter/generators;
2. Assessment of an integrated bearing/monitoring test prototype;
3. Development of algorithms for health assessment and remaining life decisions;
4. Run experimental fatigue life tests for data generation and system validation;
5. Validation of a concept prototype for instrumented starter/generator bearings.

To effectively achieve these objectives, the work is being conducted as part of a European industrial/academic collaboration. Thales AES has initially provided a relevant bearing specification for starter/generators newest generation as a project foundation. Cranfield University is investigating health assessment and decision making algorithms. Active Space Technologies is developing and integrating the bearing test prototype; whereas bearing specialist Barden has specified and supplied the appropriate bearing design for this application. Laboratory fatigue tests and their post-examination will be conducted at Schaeffler's state of the art facilities.

By achieving these objectives, the greater following benefits will be achieved:

- Increased confidence in starter/generator availability;
- Optimised maintenance planning and cost effectiveness;
- Lower mass, leading to lower fuel consumption.

In the present paper, we present the initial developments of the on-going collaborative i-BEARING CleanSky project, funded by the European Commission. The paper structure comprises of a concise literature review covering relevant degradation mechanisms, and approaches to health management. Both, failure mode and effect (FMEA) and performance failure analyses were conducted to substantiate sensor selection and development of health management algorithms. We also present initial diagnosis algorithm validation results.

2. Literature review

2.1. Hybrid bearings degradation

To our knowledge, health management of hybrid bearings specifically for engine starter/generators has not been addressed in previous studies. This review starts by analyzing the degradation of hybrid bearings. Understanding specific bearing degradation mechanisms is a fundamental part of the health assessment approach, in order to determine what to measure and what features to extract from data.

Extensive studies have shown that a variety of hot isostatic pressed silicon nitride (Si_3N_4) grade materials produce ball bearings with several times longer RFC life than that of high-quality steel bearing steel [3]. Ceramic ball bearings predominantly fail by spalling, in very much the same fashion observed in steel bearings [4]. Micro-spalling of steel race surfaces has been observed [5]. Earlier research has mainly focused on qualifying Si_3N_4 as a robust bearing ball material. A strong emphasis has been placed in validating Si_3N_4 elements and the avoidance of catastrophic failure [6]. A recent study has validated these previous researches [7]. Hybrid bearings continue to be widely adopted by many industrial applications.

2.2. Bearing failure factors and health monitoring of electrical machines

Widely acknowledged reviews [8] on the failure of electrical machines, such as starters and generators, report that bearings account for 40-50 % of all failures. This high incidence has sparked a number of diagnostic studies, which are largely based on the use of current measurement analysis and signal processing techniques, e.g., studies by Benbouzid [9] and Elbouchikhi [10]. Nandy [8] also reported that although in-service conditions such as vibration, inherent eccentricity and electrical currents can negatively affect bearing performance, other external factors can have an even stronger influence on bearing premature failure, namely:

- Contamination and corrosion - caused by pitting and sanding action of hard abrasive minute particles or corrosive action of water, acid, etc.;
- Improper lubrication - both under and over lubrication can cause abrasion and heating;
- Improper installation - poor installation practices can result in misalignment and eventually pitting or brinelling.

Tandon [11] conducted a diagnostic study on electrical machines to determine the most sensitive sensors for bearing fault detection. A range of monitoring techniques that included electrical signatures monitoring, vibration, acoustic emissions (AE), and shock pulse method (SPM) were compared. Those tests consisted in running induction motors fitted with conventional steel bearings with seeded defects on the outer raceways. The size of the defects varied from 250 μm to 1.5 mm, while the load also varied from 0 to 27 kg at a constant speed of 1400 rpm. Results were expressed as a function of the signal percentage increase with respect to average of healthy bearing, for the smallest defect. Their experiments showed that both AE and SPM measurements had a considerable higher response than other techniques. Those results are invaluable for our research since they identify the most effective sensors for earliest detection: AE and analysis of high frequency vibrations.

2.3 Bearing health management algorithm review

Unlike conventional rolling element bearings, examination of literature on hybrid bearings showed a small number of publications addressing diagnosis and prognosis [14,15]. Significantly, previous research has been done at lower rotational speeds than those envisioned for the newest generation of starter generators (1800 vs. 30,000 rpm).

2.4 Diagnostics and prognostics of hybrid bearings

A crucial step for constructing an effective health management system for starter/generators is to employ the appropriate algorithmic approach. The selection of the appropriate algorithms generally responds to the application characteristics, data to be acquired and the algorithm applicability [12]. Algorithm selection can be performed in a heuristic way, using researchers' experience and expertise, or alternatively by Quality Function Deployment (QFD).

In recent times, numerous algorithms have been introduced, developed and benchmarked to process signals, using supervised or unsupervised classification, to assess the health state and to predict remaining useful life (RUL). Comprehensive reviews are widely available [12,13]. Table 1 summarises some highly relevant approaches.

Table 1: Summary of algorithms used for health management

Approach	Typical use and main characteristics
Time Domain Analysis	Analysis of waveforms.
Fourier Transform	Representation in the frequency domain.
Short-time Fourier Transform	Signal representation in both the time and frequency domains.
Wavelet Packet Energies	Representing signals in terms of a finite length or fast decaying oscillating waveform that is scaled and translated to match the input signals.
Hilbert–Huang Transform	Decomposing complicated signals into a finite number of intrinsic mode functions (IMFs) in the time domain and to represent signals with time–frequency–energy distribution.
Principal Component Analysis	Reduce dimensionality by transforming the original features into a new set of uncorrelated features.
Bayesian Networks	Directed acyclic graph tools to present the structure of conditional interdependency relations and probability distributions between variables in one system domain.
Neural Network	Simulates the structures and functions of biological neural networks; able to modelling complex relationships between inputs and outputs and finding patterns in data.
Decision Trees	Decision making data classification by starting at the root node of a tree and following assertions down until reaching a terminal node (leaf of tree).
ARMA	Consisting of two parts: autoregressive (AR) and moving average (MA) for modelling and predicting future values in a time series of data.
Fuzzy Logic	Representing and processing uncertainty: it tolerates uncertainty and can utilize language-like vagueness to offer robust, noise tolerant models, or predictions.
Support Vector Machine	Finding an optimized separation hyperplane in the projected space to maximize the decision boundary.
Hidden Markov Model	Statistical model where the system being modelled is assumed to be a Markov process with unknown state space parameters.

3. Research methodology

Our study examined the new starter/generator product specification, particularly the expected operational parameters and in-service conditions. The degradation of hybrid bearings was first examined in the literature and then by bearing experts. This helped to establish the health monitoring approach and to identify sensor technologies. Following these initial steps, bearings were specified and an instrumented bearing prototype was built for laboratory testing. Tests enable the generation of data for analysis, algorithm training and validation. Results are then feed into a new iteration of an instrumented bearing specification prototype for starter/generators. The overall research approach has been summarised in Figure 1.

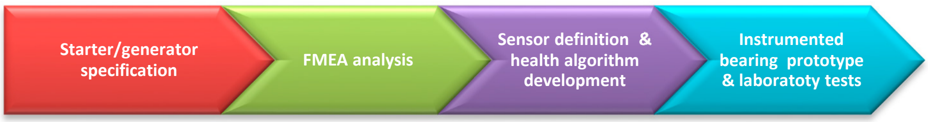

Figure 1 research overall approach

4. Failure mode and effect analysis for starter/generator hybrid bearings

The degradation analysed in the literature review was complemented with a failure mode and effect analysis (FMEA) conducted with bearing specialists based within our research partners companies.

During a series of structured team meetings, the failure modes likely to be experienced by starter/generators were comprehensively reviewed. The output of this exercise was captured using a variety of analytical tools such as mind-maps and swim lane diagrams. In the first instance, the typical failure modes have been identified and then broken down into more detail. This has identified potential causes against which relevant bearing symptoms can be attributed to. The corresponding symptoms were then analysed in consideration to potential sensing methods, either bearing mounted or in the starter/generator operating environment. In some instances, it was found that specific symptoms can be in fact another primary cause of failure.

The expertise of the team conducting the FMEA arises from working closely with customers across a range of industrial fields, including aerospace fans, motors and generators. The FMEA combined expertise of the team added up to 50 years.

The anticipated degradation mechanism can be summarised as one where a crack is generally initiated by one or more of the following: fatigue, wear, deformation, contamination, poor lubrication, high temperature or corrosion. The symptoms of the degradation progression manifest in acoustic emissions, vibration, debris and temperature. Damage will then develop from minute cracks to substantial spalling in the affected bearing elements leading to the bearing's functional failure.

To identify the bearing wear stages, the FMEA used bearing vibration as a reference. Pre-defined frequency bands were used to assess bearing condition at a given rotational speed. Three bands have been identified as function of the bearing parameters and the operational speed:

i. Low Band (typical range from 60 to 1000 Hz) -Usually representing low order harmonics of the raceway frequency and can also indicate discrete points of damage;
ii. Mid Band (typical range from 1 to 3 kHz) - Frequently representing higher order harmonics of the raceway frequency, ball damage or harmonics;
iii. High Band (3 to 10 kHz) - Usually represent an indication of contamination or affected surface finish.

The FMEA findings were used to construct a swim lane diagram that provided guidance as to when detection of a particular failure mode could be expected; from entry into service to catastrophic failure. The diagram showed potential bearing failure causes and effects, as well as operational parameters and characteristic responses that could be sensed for hybrid bearings in starter generators. Figure 2 captures a summary of this analysis findings.

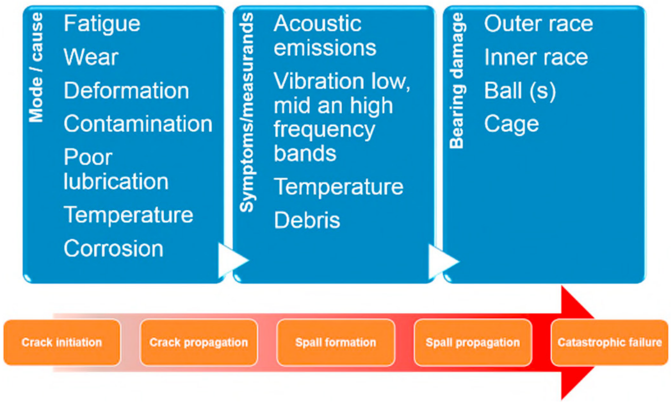

Figure 2 FMEA swim lane summary

5. Sensor selection

Sensor selection carefully considered the consortium and stakeholder's requirements, results from FMEA analysis, and literature review findings. A wide selection of sensor types, manufacturers and measurement ranges were extensively reviewed. Because this was the first time the health management of hybrid bearing in starter/generators was attempted, it has been agreed that the study would attempt monitoring and characterizing bearings degradation from as early as possible throughout to the later bearing life stages. This meant selecting acoustic emission technology and vibration enveloping analysis for monitoring bearings at the earlier stages. For the bulk of the bearings life, both frequency and time domain analyses as well as temperature monitoring have been selected. Sensors were installed in an interchangeable sleeve adaptor mounted directly on the test bearings outside diameter. This permitted testing a number of bearing samples. The sensors selected are shown in Table 2.

Table 2 Sensors selected for instrumented bearing tests

Sensor type	Measurement range
Accelerometer, tri-axial	1.5 Hz to 40 kHz
Accelerometer, uniaxial	1 Hz to 26 kHz
Acoustic emission, high frequency	200-950 kHz
Acoustic emission, low frequency	10 Hz to 500 kHz
Resistance Temperature Detector (RTD)	-50 °C to 250 °C

6. Bearing selection & test rig

The main specification characteristics of the selected test bearings included:

- Type: hybrid bearing;
- Number of balls: 19;
- Materials: Cronidur for rings, Si_3N_4 for rolling elements;
- Nominal bore diameter: 50 mm;
- Nominal outside diameter: 72 mm.

The selected instrumented test rig capabilities include:

- Rotational speed: up to 20,000;
- Load type: combining both axial and radial;
- Maximum load: up to 250 kN axial and 160 kN radial.

7. Health assessment approach

Data-fusion principles will be used for bearing diagnosis and for decision making algorithms. A collection of health condition indicators (CI) will be extracted from multiple measurements from a variety of sources. This large number of CIs describes time- domain, frequency-domain and high frequency emissions. The frequent measurements and concurrent CIs contribute a higher degree of confidence of the bearings health state diagnosis [16, 17] and replacement alarms. Figure 3 illustrates the general approach represented by a traffic light indicator.

The CIs so far considered include: Root mean square (RMS), Peak amplitude, Kurtosis, ball pass frequency (BPF), outer BPF, Inner BPF, cage frequency, AE and temperature amplitude and demodulation subroutines.

At the decision level, the algorithms aim at issuing a bearing replacement recommendation within at least a 100 hour remaining useful life. Due to importance of the application, timely, unambiguous replacement risk-based alerts are demanded. The algorithms so far considered at the various architectural levels include voting, Boolean and fuzzy logic and other probabilistic Bayesian approaches. LabVIEW has been chosen for the algorithms programming because it offers efficient data management with relevant signal processing toolkits.

8. Health assessment preliminary validation results

Preliminary evaluation of the health assessment algorithms has been conducted ahead of the experimental regime results to ensure characteristic wear features can be effectively identified. This evaluation used widely analysed NASA/IMS vibration datasets [18] and other available AE Cranfield University datasets [19]. Both datasets were produced with conventional steel bearings. An example of this process is shown in Figure 4. Results clearly showed that detection of a bearing fault by the measurement of burst amplitude. In this case, the fault refers to a seeded defect of 5 x 12 mm on the outer raceway of a larger bearing.

Validation of vibration diagnosis analyzed data from tests 1 and 3 of the NASA IMS datasets. In both cases we were able to diagnose the bearing faults originally reported by using a combination of time and frequency domain indicators.

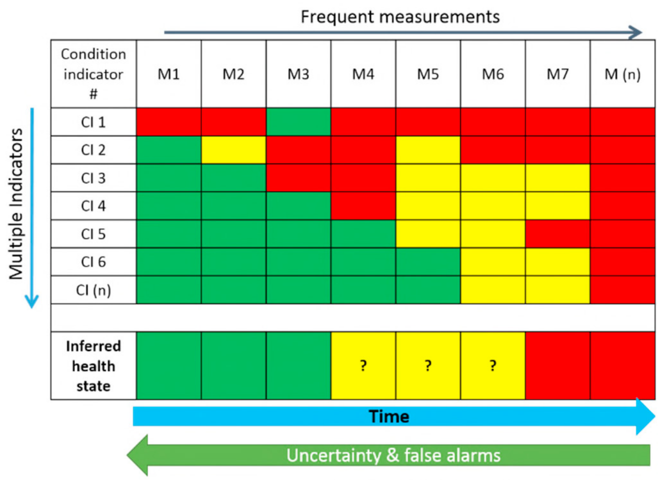

Figure 3 Degradation diagnosis approach illustration

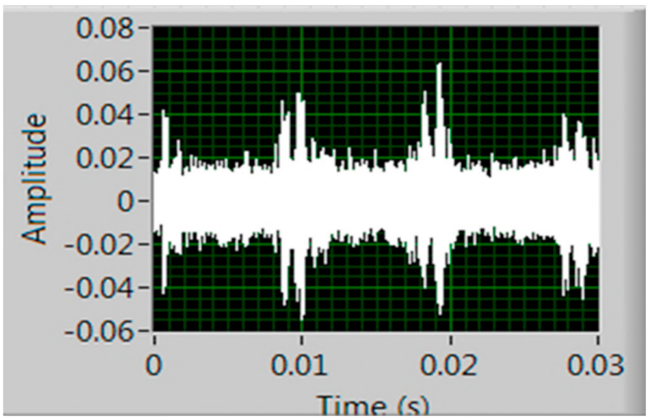

Figure 4 Acoustic emissions validation of seeded defect detection

9. Summary and Conclusions

We have identified the critical parameters and operational conditions for high speed hybrid bearings to be used in the newest generation of aircraft engines starter/generators. The likely degradation mechanisms have been thoroughly analyzed. From these, we have defined the specification of new test bearings as well as the sensing technologies for monitoring their wear behavior. Test bearing prototypes will be instrumented with accelerometers, acoustic emission sensors and RTDs. We have presented a data fusion approach to diagnose the bearings' health and to issue their replacement alarms. This approach uses data acquired from a large number of measurements conducted throughout a number of bearing fatigue tests carried out in industrial state of the art facilities. By using signal processing techniques, a number of time and frequency domain indicators will be extracted. The data-fusion processes will enhance bearing wear and fault diagnosis; and will enable risk-based, low uncertainty and false-alarm ratio replacement alerts. Initial results have shown our diagnosis algorithm can effectively identify labelled diagnosis characteristics on available NASA/IMS vibration and local AE datasets.

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